DOES TEACHER MULTICULTURAL TRAINING MATTER? EVIDENCE FROM THE U.S. SCORES ON PISA 2015.

by
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Abstract

The racial and ethnic achievement gap in the USA ranges from about 3 to 5 years of schooling. Existing research about diversity in education has focused on studying the effect of matching students with teachers of the same culture or gender, and the different mechanisms that mediate those effects, including bias, stereotypes and prejudices. Multicultural competence training has been an essential part of work training and professional development in the military and business industries. In the field of teacher education, it has also been discussed and incorporated to some extent but there is no research about the effectiveness of the training and its impact on student performance. This study takes opportunity of the new teacher questionnaire from PISA 2015, a large-scale international assessment study administered every 3 years to 15-year-old children around the world to measure their performance in reading, math and science. Using multilevel analysis, the effect of multicultural training on the student's performance in science was measured for immigrant and native students in the USA. The results show that multicultural training has no significant effect on student performance in science, even after accounting for the economic, social and cultural status of students and schools, and common indicators of teacher quality.

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Introduction

About 25% of the children in the Unites States were first or second-generation immigrants in 2014, a 45% increment in 10 years according to Child Trends[1]. The racial and ethnic achievement gap, a measure of inequality in education, has been steadily declining since 2005[2]. Nevertheless, the numbers are still very high, ranging from 0.5 to 0.9 of a standard deviation, which is equivalent to 2.8 to 5 school years of schooling[3]. Part of this gap could be attributed to the socioeconomic characteristics of these groups, but an extensive body of research has found differences in achievement that are directly associated with other characteristic of the students like race, culture and gender. Except for Antecol, Eren and Ozbeklik[4] who find that having a female teacher lowers the math test scores of female disadvantaged students on primary school, all other research argues that the match of teacher and student of the same race and/or the same gender has a positive and non trivial effect on educational outcomes.

Although most of these studies fail to explain the mechanisms behind the effect of race/gender matching of student and teachers on academic performance, there is some evidence that it can be explained in part by cultural stereotypes that influence teacher

[1] Child Trends Data Bank, Indicators of Child and Youth Wellbeing, 3.
[2] CEPA, Racial and Ethnic Achievement Gaps. Hansel, Mann and Quintero, Have We Made Progress on Achievement Gaps.
[3] Based on the general rule of thumb that 1 percent of a standard deviation of performance is roughly equivalent to 10 days of schooling (Carlsson, Gordon and Bjorn, The Effect of Schooling on Cognitive Skills, 533).
[4] Antecol, Eren and Ozbeklik, The Effect of Teacher Gender on Student Achievement, 63.

expectations on student achievement and class interactions. This evidence has moved education reformers and policy makers into two directions. The first one is to promote an increase in teacher diversity[5]. This is not always a viable solution due to the natural demographic differences among children and adults and teacher shortage, among other reasons[6]. Also, in a segregated school system, matching teachers with students would increase teacher segregation, which would additionally perpetuate the problem of wrong beliefs and stereotypes. Furthermore, in a demographic match scenario, bias may be smaller (especially for the biggest minorities) but is still present[7]. A higher-level goal is to reduce or eliminate bias for all students by developing teacher cross-cultural competence. Many school districts already require that their teachers take multicultural training courses during their teacher training or as a professional development activity. In fact, about 77% of the teachers in our sample had either professional training, or professional development, or both in teaching in a multicultural classroom. This study found that having a higher proportion of teachers with multicultural training in the schools does not change the academic performance in science of the general population of 15-years old students or the performance of the 15-years old population of immigrant students. This is a very important finding and it may help explain why the achievement gap have decreased so little despite the considerable amount of education reforms designed with that goal in mind. This study does not suggest that teacher multicultural competence is

[5] Casey, Di Carlo, Bond and Quintero, The state of teacher diversity in American Education.
[6] Hansen and Quintero, 4 Ways to Measure Diversity Among Public School Teachers.
[7] Except in the long room, where teachers and students could increase their cross-cultural knowledge due to the increased interaction.

not an attainable and important policy goal. On the contrary, it suggests that other ways to increase multicultural competence must be explored. We also find that school characteristics have a big role in explaining student differences in performance that are not related to a student's individual differences and that school average socio-economic status is an important indicator of student success. The latter are no new findings but nevertheless there have been very few efforts made to decrease segregation in American schools.

The next section includes a review of the literature, followed by a description of the data and the methods used in the analysis. The third section present the results, which are further discussed in the last chapter together with their public policy implication and suggestions for future research.

Literature Review

A growing body of research on education, social psychology and labor economics has attempted to understand the effect of teacher race and gender on student achievement at the elementary and secondary levels[8], and at the college level[9]. Burgess and Greaves[10] find evidence of systematic white-ethnic minority differences between quasi-blind and non-blind testing within schools. Using a longitudinal study, Dee[11] finds that assignment to an opposite-gender teacher lowers student achievement by nearly 0.05 of a standard deviation. In a different study, Dee[12] finds that random assignment to own-race teachers in elementary schools in Tennessee was associated with a 3 to 6 percentile point increase in test scores. Using the same data source, Ehrenberg, Goldhaber and Brewer[13] find little evidence of an association between own-race, ethnicity and gender of the teacher and test scores but they do find a correlation between gender/race matching and higher subjective evaluations. Gershenson, Holt and Papageorge[14] find that non-black teachers of black students have 12% lower expectations of student educational attainment than do black teachers. Ouazad[15] presents evidence that teachers give better assessments to students of their own race as early as in kindergartner. Gong and Lu[16], using a nationally representative survey of teachers and students in China, find that having a female teacher has positive and significant effects on girls' academic and noncognitive outcomes relative

[8] Gong and Lu, The Effect of Teacher Gender; Antecol, Eren and Ozbeklik, The Effect of Teacher Gender on Student Achievement; Dee, Teachers, Race, and Student Achievement; Dee, , Teachers and the Gender Gaps; Ehrenberg, Goldhaber, and Brewer, Do Teachers' Race, Gender, And Ethnicity Matter; Farkas, Sheehan, Grobe, and Shuan, Cultural Resources and School Success; Lim & Meer, The Impact of Teacher–Student Gender Matches; Ouazad, , Assessed by a Teacher Like Me.
[9] Fairlie, Hoffmann, and Oreopoulos, A Community College Instructor Like Me; Hoffmann and Oreopoulos, A Professor Like Me; Carrell, Page, and West, Sex and Science.
[10] Burgess and Greaves, Test Scores, Subjective Assessment, and Stereotyping of Ethnic Minorities.
[11] Dee, Teachers and the Gender Gaps in Student Achievement, 550.
[12] Dee, Teachers, Race, and Student Achievement in a Randomized Experiment, 202.
[13] Ehrenberg, Goldhaber and Brewer, Do Teachers' Race, Gender, And Ethnicity Matter, 559.
[14] Gershenson, Holt and Papageorge, Who Believes in Me, 220.
[15] Quazad, Assessed by a Teacher Like Me, 334.
[16] Gong and Lu, The Effect of Teacher Gender, 775.

to those of boys. Lim and Meer[17] reach very similar results in their study of middle school students in South Korea.

The mechanism that mediate the relationship between race, ethnicity and gender, and academic achievement has also been studied to a lesser extent. In the first theory, the teachers play a passive role acting as “role models” for their students. Researchers argue that same gender/ethnic group teachers can inspire their students to believe that they can achieve to perform as well as their teacher, especially among minority students. In this case, the change in attitudes toward learning comes from the student own stereotypes and perceptions about culture and gender. Klopfenstein[18] explored the student enrollment on advanced math classes and found a positive impact of opposite-sex black teachers on the likelihood that a black geometry student will enroll in a subsequent rigorous math course. Gong and Lu[19] also found evidence of the positive “role model” effect when middle school girls in China were randomly assigned to same female teachers.

Another theory explores the role of stereotypes from the teacher side and how they influence teacher attitudes and expectations about their students. In a highly segregated sample of elementary student and teachers in Michigan in 1979, Beady and Hansell[20] found that black teachers had significantly higher expectations for the future success of their students in college than white teachers. More recently, Gershenson, Holt and

[17] Lim and Meer, The Impact of Teacher–Student Gender Matches, 979.
[18] Klopfenstein, Beyond Test Scores, 424.
[19] [19] Gong and Lu, The Effect of Teacher Gender, 764-769.
[20] Beady & Hansell, Teacher Race and Expectations for Student Achievement, 202.

Papageorge[21] find that high school non-black teachers of black students have significantly lower expectations than do black teachers. Burgess & Greaves (2013) argue that teachers form expectations of students that belong to an ethnic group based on the past academic performance of other students of the same group. In a similar way, Riegle-Crumb and Humphries[22] find evidence of a small bias against white female math student, which is associated with the belief that math is easier for white males than it is for white females. Gong, Lu and Song findings support both the stereotype threat hypothesis and role model theories.

All these research points to the problem of teacher/student bias and the negative effect on the race and gender achievement gap. Research on Social psychology has explored different mechanisms for reducing bias, stereotypes and prejudices[23] but no empirical research has been done on the effect of the increase in awareness of the teacher's own bias and stereotypes (which I conceptualize as cross-cultural competence[24]) on student achievement. One reason may be the difficulty of assessing cross-cultural competence and finding related data on student achievement. This study attempts to fill that gap by exploring the effect of teacher education or training in teaching in a multicultural or

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[21] Gershenson, Holt, and Papageorge, Who Believes in Me,

[22] Riegle-Crumb and Humphries, Exploring Bias in Math Teachers' Perceptions of Students' Ability, 312.

[23] Devine, Forscher, Austin and Cox, Long-term reduction in implicit race bias; Paluck and Green, Prejudice reduction: What works; Dasgupta and Asgari, Seeing is believing: Exposure to counterstereotypic women leaders; Rudman, Ashmore and Gary, Unlearning" automatic biases.

[24] For a theoretical view of cross-cultural competence see Deardorff, Intercultural competence; Deardorff & Arasaratnam-Smith, Intercultural Competence in Higher Education; Mcallister & Irvine, Cross Cultural Competency.

multilingual setting on the achievement gap between immigrant and non-immigrant students on the PISA test of 2015.

Data and Methods

This study uses the Programme for International Student Assessment (PISA) which is a survey designed by the Organization for Economic Co-operation (OECD) to evaluate education systems worldwide. It includes student and school background information and an assessment made every three years to a representative sample of 15-year-old students on core school subjects of mathematics, reading and science. PISA 2015 focuses most of the assessment on science and includes for the first time a questionnaire for the science teachers. For this research, data for the United States will be extracted and combined from three datasets: a student questionnaire with 921 fields and 519,334 records, a school questionnaire with 273 fields and 17,908 records, and a teacher questionnaire with 253 fields and 108,292 records. PISA 2015 used a complex sample design where schools are randomly selected first and subsequently, 15-year-old student where randomly selected.

Dependent Variable

PISA surveys report student performance through plausible values (PVs). This is an estimator used to measure the performance of a population and not suitable to measure the performance of an individual student. They are used, instead of raw test scores, to account for the substantial measurement errors that occur on education measures[25]. Adams and Wu[26] explain the concept of plausible values in the following way:

> *They are random numbers drawn from the distribution of scores that could be reasonably assigned to each individual—that is, the marginal posterior distribution... As such, plausible values contain random error variance components and are not optimal as scores for individuals. Plausible values as a set are better suited to describing the performance of the population… Plausible values are intermediate values provided to obtain consistent estimates of population parameters…*

PISA 2015 student dataset contains 10 plausible values per student for every scale. To obtain statistics or perform regression analysis using plausible values, each statistic or equation must be calculated 10 times, once with each PV variable. Then the results are averaged, and the significance tests adjusted for the variation between the 10 results.

This study uses the previous method for the exploratory part of the analysis using SPSS Statistics and IDB Analyzer[27]. For the regression analysis, only one PV for science (***PV1SCIE***) is used as the dependent variable. This is because SPSS Statistics cannot deal with fractional weights and the alternative of using SAS is out of the scope for this study[28].

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[25] See OECD (2009, p.75-80).
[26] Adams and Wu, PISA 2000 Technical Report, 107.
[27] IDB Analyzer is an application developed by the International Association for the Evaluation of Educational Achievement (IEA) that can be used to combine and analyze data from most major large-scale assessment surveys.
[28] See PISA Data Analysis Manual (2009, p.185). The R package intsvy offers the possibility to perform the analysis but it doesn't include the teacher questionnaire (new dataset for 2015) where the independent variable of interest is located. The pisatools package from STATA seems to have the same problem as it was developed in 2013.

Therefore, results must be considered as preliminary where all significant tests may be positively bias[29].

Analyses

A multilevel linear model (MLM) mixed-model procedure was used for this study to account for the hierarchical structure of the data and the different levels of analysis of the variables of interest[30]. The SPSS Statistics software was used to conduct the analysis with unrestricted maximum likelihood and unstructured covariance type for the random effects.

The first step in the analysis is to derive and compute the intercept-only model[31] and compute the intraclass correlation. The objective is to find how much of the variation of the dependent variable at the student level is explained by the variation at the school level. The regression model (equation 3) is derived from equations 1 and 2:

$$\text{Student level: } \boldsymbol{PV1SCIE_{ij} = \beta_{0j} + e_{ij}} \qquad (1)$$

Where $\boldsymbol{PV1SCIE_{ij}}$ is the Plausible Value 1 in science for the *ith* student in the *jth* school, β_{0j}, the regression intercept, represents the mean science score for the *jth* school and e_{ij}, the residual error term, represents the individual student difference around the *jth* school

[29] By omitting the sampling error, standard errors may be underestimated which would result in increased Type I errors or incorrect claims that findings are statistically significant.

[30] Traditional regression analysis with school fixed effects is not an appropriate method for this study because the independent variable of interest, teacher multicultural training or professional development, was measured at the school level. A fixed effects model would not be able to estimate the model as all variability at the school level would have already been accounted for. See Huang (2014).

[31] Also called empty model because it does not include explanatory variables.

mean. The subscript *j* represents the schools (*j=1…J*) and the subscript i represent the students (*i=1…n_j*).

$$\text{Class level: } \boldsymbol{\beta_{0j} = \Upsilon_{00} + \mu_{0j}} \tag{2}$$

Where Υ_{10} is the grand average score that do not vary across schools, and μ_{1j} is the residual error term at the school level.

Equations 1 and 2 are combined to produce one equation:

$$\boldsymbol{PV1SCIE_{ij} = \Upsilon_{00} + \mu_{0j} + e_{ij}} \tag{3}$$

The intraclass correlation (ρ) shows the proportion of the variance explained by the schools and it is obtained with the formula:

$$\boldsymbol{\rho = \sigma^2_{\mu 0} / (\sigma^2_{\mu 0} + \sigma^2_e)} \tag{4}$$

If the variance coefficients are statistically significant and the intraclass correlation is different from zero, there is a justification to add explanatory variables at the student and school level. The independent variable of interest on this study is "training or professional development in teaching in a multicultural or multilingual setting" (TC045Q10). This variable was collected at the teacher level but can only be identified with the school and has a value of 0 for "not existing", 1 for "only part IE", 2 for "only part of PD", and 3 for "overlap IE and PD". TC045Q10 was aggregated at the school level as a percentage of teachers with training or professional development in teaching in a multicultural or multilingual setting (PCT_MCTrain)[32]. The effect of multicultural training on students scores can only be observed at the school level, which is not ideal.

Due to the complexity of multilevel analysis, explanatory variables are added and analyzed one at a time. In this study, explanatory variables that have been previously used in other studies and proven to be statistically significant at explaining performance differences between students and schools are added first. The explanatory variable of interest, PCT_MCTrain, was added to the second model and other variables that may be mediating the effect of multicultural training on student performance in science were subsequently added one at a time. Again, due to the amount of interactions, variables that were not statistically significant, other than multicultural training, were discarded from the model. Finally, the dummy variable IMMIG with a value of 0 for non-immigrant students and 1 for first- and second-generation immigrant students, was included in the final model.

[32] PCT_MCTrain = Percentage of TC045Q10 values above zero.

Results

Table 1 reports the summary statistics for all continuous variables used in the study. The sample size of 5,239 students is the result of listwise deletion of all missing cases on the variables of interest from the original sample of 5,712 USA students. The statistics on table 1 are unweighted but the regression analysis used the student final weights after adjusting for the listwise deletion. Between 60% and 94% of the teachers in the schools that this sample of students attended in 2015 had some kind of training in teaching in a multicultural classroom, and 10% to 47% of the teachers had training during their teacher education program and during professional development activities. Both variables where used in the analysis and the results are very similar. Only the results for PCT_MCTrain will be presented in this paper.

Table 2 presents the parameter estimate and standard errors for all models. The intercept-only model estimates the intercept as 499, which is the average test score on science for all schools and pupils. The variance of the student level residual error (σ^2_e) is estimated at 7,757.52. The variance of the school level residual error ($\sigma^2_{\mu 0}$) is estimated at 1,678.33. All coefficients are significant at p<0.001. The significantly high coefficients of the variance are an indicator of the need to add explanatory variables at both levels. The intraclass correlation ($\rho = \sigma^2_{\mu 0} / (\sigma^2_{\mu 0} + \sigma^2_e)$), which represents the proportion of the variance in science scores explained by the school, equals 17.79%. As a comparison, the intraclass correlation in science in 2015 for all countries tested by PISA ranged from 3.8 in Iceland to 55,4 in Hungary, and high performing countries tend to have smaller intraclass correlations [33]. The deviance is a measure of the model misfit and is expected to go down when explanatory variables are added.

Table 1: Summary Statistics - Unweighted

Variables	**N**	**Mean**	**SD**
Student Level Variables			
Plausible Value 1 in Science (***PV1SCIE***)	5,239	500.18	96.56
Index of economic, social and cultural status (***ESCS***)	5,239	0.10	1.00
School Level Variables			
% of teachers with training **or** professional development **or** both in teaching in a multicultural classroom (***PCT_MCTrain***)	5,239	77.24	17.16
% of teachers with training **and** professional development in teaching in a multicultural classroom	5,239	28.60	18.20
Mean years of experience (***Mean_Exp***)	5,239	14.17	3.31
Percentage of teachers with Master degree or higher	5,239	61.84	21.17
Percentage of teachers trained in science	5,239	45.67	11.66
Percentage of originally trained teachers	5,239	36.69	14.20
School mean of Index of economic, social and cultural status (***MU_ESCS***)	5,239	0.10	0.53

The second model (M1) includes an index of economic, social and cultural status (ESCS) as an explanatory variable at the student level. This variable was centered around the grand mean to facilitate the interpretation of the coefficient[34]. At the school level, the school mean of ESCS is used as an explanatory variable. These two variables are commonly used in multilevel analysis of education. The interaction variables in the table are the result of combining the student and school level equations as follows:

$$\textit{Student level: } PV1SCE_{ij} = \beta_{0j} + \beta_{1j}\,(CESCS_{ij}) + e_{ij} \tag{5}$$

$$\textit{School level: } \beta_{0j} = \Upsilon_{00} + \Upsilon_{01}\,(MU\_ESCS_{j}) + \mu_{0j} \tag{6}$$

$$\beta_{1j} = \Upsilon_{10} + \Upsilon_{11}\,(MU\_ESCS_{j}) + \mu_{1j} \tag{7}$$

[33] See OECD (2017, p. 93)
[34] See Fox et al. (2010, p. 59-63) and OECD (2009, p. 193)

$$Combined: PV1SCE_{ij} = \Upsilon_{00} + \Upsilon_{01}\,(MU\_ESCS_j) + \Upsilon_{10}\,(CESCS_{ij}) + \Upsilon_{11}\,(MU\_ESCS_j{*}CESCS_{ij}) + \mu_{1j}(CESCS_{ij}) + \mu_{0j} + e_{ij} \qquad (8)$$

All coefficients in model 1 are statistically significant at conventional levels and the deviance is smaller which imply that it is a better model compared to model 0. The coefficient of the intercept (492.42) is 6.56 points smaller compared to the empty model. This means that when the ESCS of a student equals the average ESCS of the population, test scores are 6.56 points lower than the average score. The coefficient of CESCS equals 23.53. Note that this variable is the student index of economic, social and cultural status that was centered around the school mean. Therefore, β_{1j} = 23.53 means that for one-point increase above the school average ESCS, science scores are expected to increase by 23.53 points. The coefficient of MU_ESCS equals 34.87, which means that for a point increase in the school average ESCS, the school average science scores are expected to increase by 38.87 points. The variance of the school level intercept is 747.72 and is statistically significant. The variance of the CESCS coefficient ($\sigma^2_{\mu 1}$ =75.16) is not significant at the 5% level (Z = 1.79, sig = .074) and therefore could be set as constant for the following models. Nevertheless, because the variance of the coefficient of the intercept ($\sigma^2_{\mu 0}$= 747.72) is high and significant, and the covariance of the two coefficients ($\sigma^2_{\mu 01}$ = 97.74) is also significant, the coefficient of CESCS will continue to be treated as random in the following models.

Table 2: Empty Model (M0), Model with random CESCS & fixed MU_ESCS (M1), Model with M1 + fixed PCT_MCTrain (M2), Model with M2 + random IMMIG (M3)

Model:	M0	M1	M2	M3[d]
Fixed part[a,b]	**Coefficient (s.e.)**	**Coefficient (s.e.)**	**Coefficient (s.e.)**	Coefficient (s.e.)
Intercept	498.98* (3.46)	492.42* (2.64)	488.98* (11.67)	504.97* (23.91)
CESCS		23.53* (1.60)	5.75(7.07)	10.51 (13.87)
MU_ESCS		34.87* (4.93)	35.47* (5.16)	24.53* (7.79)
MU_ESCS CESCS*		10.79* (2.73)	13.38* (2.83)	11.06* (5.72)
PCT_MCTrain			.04(.15)	-.17 (.29)
*PCT_MCTrain*CESCS*			.23* (.09)	.16 (.17)
IMMIG				-23.13 (25.17)
$MU\_ESCS_j*IMMIG_{ij}$				17.31* (8.35)
$PCT\_MCTrain_j*IMMIG_{ij}$				.31 (.30)
Random part[a,b]				
σ^2_e	7,757.52* (154.01)	7,237.83* (145.9)	7,244.07* (146.13)	4,397.42* (59.89)
$\sigma^2_{\mu 0}$	1,678.33* (217.13)	747.72* (113.45)	723.49* (123.48)	573.63* (356.34)
$\sigma_{\mu 0 1}$		97.74* (48.83)	100.35* (47.52)	-6.55c (.00)
$\sigma^2_{\mu 1}$		75.16 (42.02)	60.94* (40.35)	1,097.51c (.00)
$\sigma_{\mu 02}$				490.45 (495.03)
$\sigma_{\mu 12}$				56.55c (.00)
$\sigma^2_{\mu 2}$				736.12c (.00)
Deviance	62,434	62,005	61,999	62,778

a. Dependent variable: Plausible Value 1 in Science (PV1SCIE).
b. Residual is weighted by FINAL TRIMMED NONRESPONSE ADJUSTED STUDENT WEIGHT.
c. This covariance parameter is redundant. The test statistic and confidence interval cannot be computed.
d. SPSS shows a warning: Interaction was terminated but convergence has not been achieved. The MIXED PROCEDURE continues despites this warning. Subsequent results are based on the last iteration. Validity of the model fit is uncertain.
*. Statistically significant at 5%.

In model 2, the independent variable of interest (PCT_MCTrain $_j$) is added to the school level equations as follows:

$$\textit{Student level: } PV1SCE_{ij} = \beta_{0j} + \beta_{1j}\,(CESCS_{ij}) + e_{ij} \tag{9}$$

$$\textit{School level: } \beta_{0j} = \Upsilon_{00} + \Upsilon_{01}\,(MU\_ESCS_j) + \Upsilon_{02}\,(\text{PCT\_MCTrain}_j) + \mu_{0j} \tag{10}$$

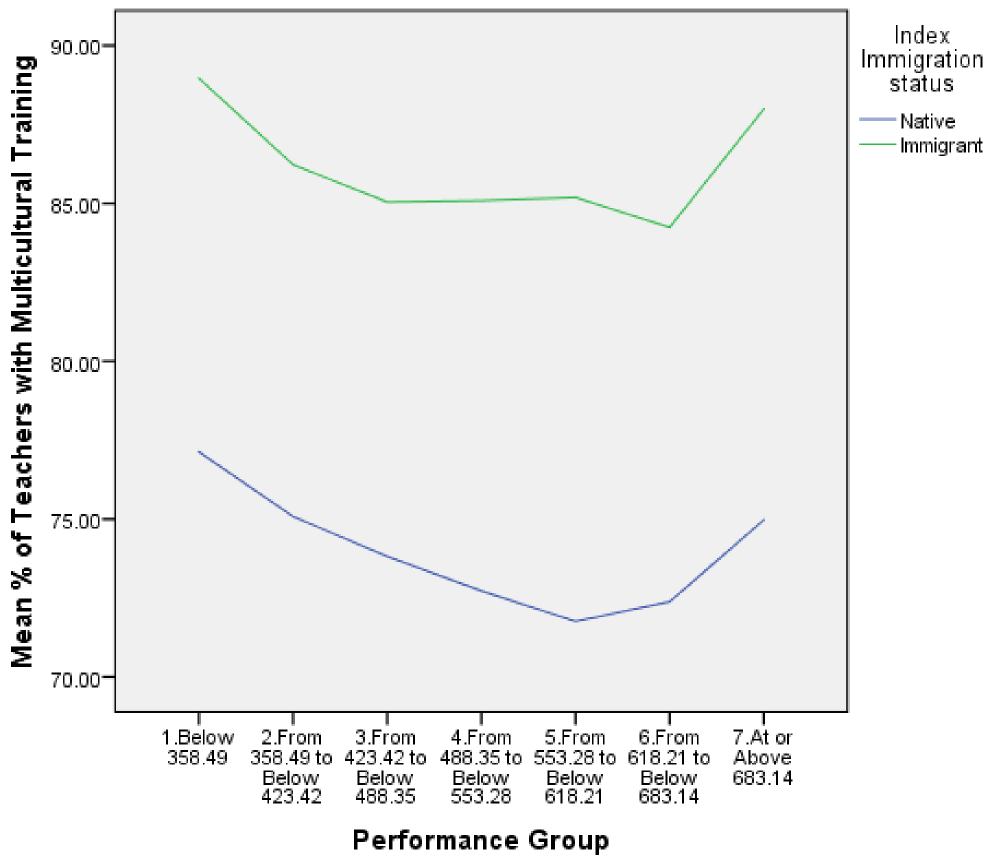
$$\beta_{1j} = \Upsilon_{10} + \Upsilon_{11} (MU\_ESCS_j) + \Upsilon_{12} (\text{PCT\_MCTrain}_{j}) + \mu_{1j} \tag{11}$$

$$\text{Combined: } PV1SCE_{ij} = \Upsilon_{00} + \Upsilon_{01} (MU\_ESCS_j) + \Upsilon_{02} (\text{PCT\_MCTrain}_{j}) + \Upsilon_{10} (CESCS_{ij}) + \Upsilon_{11} (MU\_ESCS_j{*}CESCS_{ij}) + + \Upsilon_{12} (\text{PCT\_MCTrain}_{j}{*}CESCS_{ij}) + \mu_{1j}(CESCS_{ij}) + \mu_{0j} + e_{ij} \tag{12}$$

The slightly smaller deviance (61,999) indicates that adding PCT_MCTrain may marginally improve the model, but this is not supported buy the near zero, non-significant values of the PCT_MCTrain and its interaction with CESCS. The cross-level interaction between PCT_MCTrain and CESCS is nevertheless significant and positive, which means that the effect of multicultural training on scores is mediated by the student cultural, social and economic status; students with higher CESCS may benefit more from having a higher proportion of teachers with multicultural training.

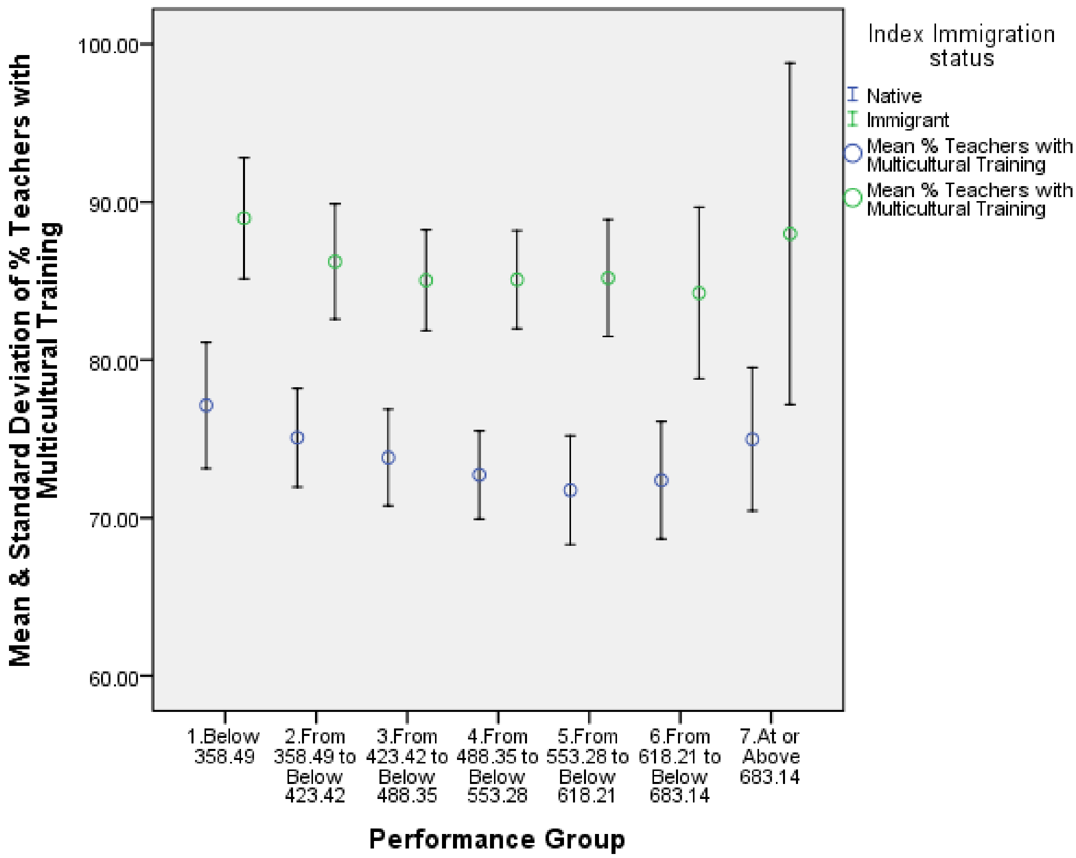
The following graphics were made with IDB Analyzer using all 10 plausible values in science and 80 replicate weights. Figure 1 shows that native students attend schools with a much lower percentage of teachers with multicultural training compared to immigrant students, which may be an indicator of school segregation. The graphic also shows that the relationship between multicultural training and performance has a U shape. This suggest that the relationship between academic performance and teacher multicultural training could not be explained with a linear regression. It also suggests that there may be other school characteristics moderating the relationship between performance and multicultural training.

Figure 1: Multicultural Training by Performance on Science for Native and Immigrant Students



In figure 2, the standard error of multicultural training was plotted against the 6 science performance benchmarks. The figure shows that immigrant student performing at the two highest benchmarks have the highest standard errors for the independent variable. This also suggest that there may be other characteristics explaining the performance differences among immigrant and non-immigrant students.

Figure 2: Standard Error of Multicultural Training by Performance on Science for Native and Immigrant Students



Other school level variables that may have an effect on scores and may change the effectiveness of the teacher training were added to the model but none of them had a significant effect on scores or varied significantly among schools. The variables tested included mean teacher experience, percentage of teachers with a master's degree or higher, percentage of originally trained teachers, and percentage of teacher with training in science. Only the results of adding teacher experience and an interaction term of teacher experience with multicultural training are presented in the appendix.

In order to see if multicultural training becomes significant for immigrant students, model 3 includes the student level dummy variable IMMIG which has a value of 0 for non-immigrant students and 1 for first- and second-generation immigrant students and is shown in equations 13 to 17.

$$\textit{Student level: } PV1SCE_{ij} = \beta_{0j} + \beta_{1j}(CESCS_{ij}) + \beta_{2j}(IMMIG_{ij}) + e_{ij} \tag{13}$$

$$\textit{School level: } \beta_{0j} = \Upsilon_{00} + \Upsilon_{01}(MU\_ESCS_j) + \Upsilon_{02}(PCT\_MCTrain_j) + \mu_{0j} \tag{14}$$

$$\beta_{1j} = \Upsilon_{10} + \Upsilon_{11}(MU\_ESCS_j) + \Upsilon_{12}(\mathrm{PCT\_MCTrain}_j) + \mu_{1j} \tag{15}$$

$$\beta_{2j} = \Upsilon_{20} + \Upsilon_{21}(MU\_ESCS_j) + \Upsilon_{22}(\mathrm{PCT\_MCTrain}_j) + \mu_{2j} \tag{16}$$

$$\textit{Combined: } PV1SCE_{ij} = \Upsilon_{00} + \Upsilon_{01}(MU\_ESCS_j) + \Upsilon_{02}(\mathrm{PCT\_MCTrain}_j) + \Upsilon_{10}(CESCS_{ij}) + \Upsilon_{11}(MU\_ESCS_j{*}CESCS_{ij}) + \Upsilon_{12}(\mathrm{PCT\_MCTrain}_j{*}CESCS_{ij}) + \Upsilon_{20}(IMMIG_{ij}) + \Upsilon_{21}(MU\_ESCS_j{*}IMMIG_{ij}) + \Upsilon_{22}(\mathrm{PCT\_MCTrain}_j{*}\,IMMIG_{ij}) + \mu_{1j}(CESCS_{ij}) + \mu_{2j}(IMMIG_{ij}) + \mu_{0j} + \mu_{1j} + \mu_{2j} + e_{ij} \tag{17}$$

Neither the coefficient of IMMIG or the coefficient of its interaction with PCT_MCTrain are significant. We will talk about the implications of this result in the discussion section. The interaction of IMMIG with MU_ESCS is nevertheless significant and positive, which shows that the effect of being an immigrant student on test scores is mediated by the school mean ESCS. Test scores for immigrant students increases on average 17 points when the school ESCS increases 1 point. That said, SPSS Mixed procedure in model 3 resulted in an error message that results in uncertainty of the validity of the model fit.

Conclusion

An intraclass correlation of 18% support previous findings[35] that differences in school characteristics have a significantly high effect on student outcomes. Changing school characteristics requires in general much less resources and is politically more feasible that changing student characteristics like income, culture, or parent involvement; or neighborhood characteristics like travel time to school and criminality rates. It is out of the scope of this paper to discuss the specific school characteristics that have an effect on scores but our findings support previous evidence of the student's social, economic and cultural status have a significant effect on academic performance and explain differences among students, as well as the average ESCS of the school. Again, reducing school segregation is considerably cheaper than leveling the ESCS of the individual students, but this is not always politically feasible. In fact, small changes in school boundaries to reduce school segregation is more frequently than not confronted with the opposition of the parents and communities on the high ESCS side of the boundary.

[35] Woessmann, The importance of school systems, 27. He specifically find that school characteristics related to quality (like instruction time and teacher quality) and not necessarily related to school resources, have the most predictive power.

The small and non-significant coefficient of PCT_MCTrain for the model that looks at the whole population of students (model 2) and for the model that differentiates between immigrant and non-immigrant students (model 3), means that the effect of having more teachers with multicultural training does not have any effect on the student academic performance. In other words, we can conclude that schools that hire more teachers with multicultural training or require teachers to take professional development classes in the area, will not see an increase on the academic outcomes of their individual students on average or for the average immigrant students in particular. Resources invested in training teachers to gain multicultural competency could be used by school districts to support school desegregation, which this and other research have proven to be an effective way to reduce the achievement gap and could be, in the long run, an effective way to increase teacher exposure to students of different backgrounds.

The fact that multicultural training is not an effective way to increase multicultural competencies does not imply that the latter is not an attainable and important goal in education policy. Instead, we propose to possible implications that need to be further studied: One is that training and professional development themselves may not be effective ways to increase multicultural competence. The second is that the characteristics of the training (content, techniques, number of hours, etc.) are not effective. This goes in hand with the more resent theoretical approaches of multicultural competence where the construct is explained as a complex and dynamic process[36]. To

[36] See Hammer (2015)

account for the complexity and dynamic nature of this skill, schools could redesign the k-12 curriculum and the teacher training curriculum to reflex the goal of making both teachers and students globally competent citizens. This idea is also the vision of the Center of Global Education of the Asia Society[37], the Graduate School of Education at Harvard[38] and many experts in the area, including Professor Laurence Peters from Johns Hopkins School of Education. The OECD is also preparing to asses the students for Global Competence starting from PISA 2018[39].

A very important limitation of this study is that it doesn't include specific information about the characteristics or quality of the training programs. It is possible that most multicultural training courses in the USA focus on teaching culture-specific knowledge instead of culture-general competencies. From the teacher questionnaire it is not possible to differentiate between a one-day professional development class and a graduate level, full semester study abroad. Another limitation is the absence of information about the student's specific cultural background, other than the immigration status. It is not possible find, for example, if multicultural training has an effect on African-American students.

The results from this article demonstrate the need for a new research agenda analyzing the characteristics of the multicultural training programs that may prove more effective in helping the teachers be more aware of their own bias and stereotypes and that would

[37] www.asiasociety.org
[38] https://globaled.gse.harvard.edu
[39] OECD (2018)

give them the competencies to inspire students from all cultural, socio-economic and neurological backgrounds. With PISA data it possible to apply the technique of this analysis to other countries to compare the results, taking into account country differences in the school systems and cultural compositions of the schools and neighborhoods. Other possibility is to exploit the student questionnaire responses about classroom interactions to find evidence of the mechanisms behind the relationship between multicultural competence and academic performance.

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Appendix

Table 3: Empty Model (M0), Model with random CESCS & fixed MU_ESCS (M1), Model with M1 + fixed PCT_MCTrain (M2), Model with M2 + fixed Mean_Exp (M3), Model with M3 + PCT_MCTrain*Mean_Exp (M4), Model with M3 + random IMMIG (M5)

Model:	M0	M1	M2	M3	M4	M5!
Fixed part[a,b]	**Coefficient (s.e.)**	**Coefficient (s.e.)**	**Coefficient (s.e.)**	**Coefficient (s.e.)**	**Coefficient (s.e.)**	**Coefficient (s.e.)**
Intercept	498.98* (3.46)	492.42* (2.64)	488.98* (11.67)	455.92* (15.88)	453.38* (37.73)	479.91* (29.76)
CESCS		23.53* (1.60)	5.75 (7.07)	-5.99 (10.24)	-30.09 (26.74)	-4.90 (19.59)
MU_ESCS		34.87* (4.93)	35.47* (5.16)	31.12* (5.24)	32.12* (5.34)	21.13* (8.16)
MU_ESCS CESCS*		10.79* (2.73)	13.38* (2.83)	12.01* (2.92)	12.68* (2.97)	9.0 (6.01)
PCT_MCTrain			.04 (.15)	.06 (.14)	.39 (.50)	-.16 (.28)
*PCT_MCTrain*CESCS*			.23* (.09)	.24* (.09)	.58 (.34)	.16 (.17)
Mean_Exp				2.27 (.75)	3.71 (2,45)	.18 (.13)
*Mean_Exp*CESCS*				.79 (.48)	2.4 (1.71)	1.08 (.92)
*PCT_MCTrain*Mean_Exp*					-.0 (.03)	
*PCT_MCTrain*Mean_Exp*CESCS*					-.0 (.02)	
IMMIG						-24.37 (31.94)
*IMMIG*MU_ESCS*						17.09* (8.25)
*IMMIG*PCT_MCTrain*						.31 (.30)
*IMMIG*Mean_Exp*						.07 (1.4)
Random part[a,b]						
σ^2_e	7,757.52* (154.01)	7,237.83* (145.9)	7,244.07* (146.13)	7,244.96* (146.14)	7242.54* (146.05)	
$\sigma^2_{\mu 0}$	1,678.33* (217.13)	747.72* (113.45)	723.49* (123.48)	669.44* (103.71)	667.65* (103.31)	
$\sigma_{\mu 0 1}$		97.74* (48.83)	100.35* (47.52)	81.2 (45.03)	79.52 (44.69)	
$\sigma^2_{\mu 1}$		75.16 (42.02)	60.94* (40.35)	53.21 (39.06)	53.27 (38.78)	
Deviance	62,434	62,005	61,999	61,988	61,986	62,781

a. Dependent variable: Plausible Value 1 in Science (PV1SCIE).

b. Residual is weighted by FINAL TRIMMED NONRESPONSE ADJUSTED STUDENT WEIGHT.

*. Statistically significant at 5%.

!. SPSS shows a warning: Interaction was terminated but convergence has not been achieved. The MIXED PROCEDURE continues despites this warning. Subsequent results are based on the last iteration. Validity of the model fit is uncertain.

Model 3:

Student level: $PV1SCE_{ij} = \beta_{0j} + \beta_{1j} (CESCS_{ij}) + e_{ij}$

School level: $\beta_{0j} = \Upsilon_{00} + \Upsilon_{01} (MU\_ESCS_j) + \Upsilon_{02} (PCT\_MCTrain_j) + \Upsilon_{03}(Mean\_Exp_j) + \mu_{0j}$

$$\beta_{1j} = \Upsilon_{10} + \Upsilon_{11} (MU\_ESCS_j) + \Upsilon_{12} (\text{PCT\_MCTrain}_j) + \Upsilon_{13}(Mean\_Exp_j) + \mu_{1j}$$

Combined: $PV1SCE_{ij} = \Upsilon_{00} + \Upsilon_{01} (MU\_ESCS_j) + \Upsilon_{02} (\text{PCT\_MCTrain}_j) + \Upsilon_{03}(Mean\_Exp_j) + \Upsilon_{10} (CESCS_{ij}) + \Upsilon_{11} (MU\_ESCS_j{*}CESCS_{ij}) + + \Upsilon_{12} (\text{PCT\_MCTrain}_j{*}CESCS_{ij}) + \Upsilon_{13}(Mean\_Exp_j{*}CESCS_{ij}) + \mu_{1j}(CESCS_{ij}) + \mu_{0j} + \mu_{1j} + e_{ij}$

Model 4:

Student level: $PV1SCE_{ij} = \beta_{0j} + \beta_{1j} (CESCS_{ij}) + e_{ij}$

School level: $\beta_{0j} = \Upsilon_{00} + \Upsilon_{01} (MU\_ESCS_j) + \Upsilon_{02} (PCT\_MCTrain_j) + \Upsilon_{03}(Mean\_Exp_j) + \Upsilon_{04} (PCT\_MCTrain_j{*}Mean\_Exp_j) + \mu_{0j}$

$$\beta_{1j} = \Upsilon_{10} + \Upsilon_{11} (MU\_ESCS_j) + \Upsilon_{12} (\text{PCT\_MCTrain}_j) + \Upsilon_{13}(Mean\_Exp_j) + \Upsilon_{14} (PCT\_MCTrain_j{*}Mean\_Exp_j) + \mu_{1j}$$

Combined: $PV1SCE_{ij} = \Upsilon_{00} + \Upsilon_{01} (MU\_ESCS_j) + \Upsilon_{02} (\text{PCT\_MCTrain}_j) + \Upsilon_{03}(Mean\_Exp_j) + \Upsilon_{04} (PCT\_MCTrain_j{*}Mean\_Exp_j) + \Upsilon_{10} (CESCS_{ij}) + \Upsilon_{11} (MU\_ESCS_j{*}CESCS_{ij}) + + \Upsilon_{12} (\text{PCT\_MCTrain}_j{*}CESCS_{ij}) + \Upsilon_{13}(Mean\_Exp_j{*}CESCS_{ij}) + \Upsilon_{14} (PCT\_MCTrain_j{*}Mean\_Exp_j{*}CESCS_{ij}) + \mu_{1j}(CESCS_{ij}) + \mu_{0j} + \mu_{1j} + e_{ij}$

Model 5:

Student level: $PV1SCE_{ij} = \beta_{0j} + \beta_{1j}\,(CESCS_{ij}) + \beta_{2j}\,(IMMIG_{ij}) + e_{ij}$

School level: $\beta_{0j} = \Upsilon_{00} + \Upsilon_{01}\,(MU\_ESCS_j) + \Upsilon_{02}\,(PCT\_MCTrain_{\,j}) + \Upsilon_{03}(Mean\_Exp_j) + \mu_{0j}$

$$\beta_{1j} = \Upsilon_{10} + \Upsilon_{11}\,(MU\_ESCS_j) + \Upsilon_{12}\,(\mathrm{PCT\_MCTrain}_{\,j}) + \Upsilon_{13}(Mean\_Exp_j) + \mu_{1j}$$

$$\beta_{2j} = \Upsilon_{20} + \Upsilon_{21}\,(MU\_ESCS_j) + \Upsilon_{22}\,(\mathrm{PCT\_MCTrain}_{\,j}) + \Upsilon_{23}(Mean\_Exp_j) + \mu_{2j}$$

Combined: $PV1SCE_{ij} = \Upsilon_{00} + \Upsilon_{01}\,(MU\_ESCS_j) + \Upsilon_{02}\,(\mathrm{PCT\_MCTrain}_{\,j}) + \Upsilon_{03}(Mean\_Exp_j) + \Upsilon_{10}(CESCS_{ij}) + \Upsilon_{11}\,(MU\_ESCS_j{*}CESCS_{ij}) + + \Upsilon_{12}\,(\mathrm{PCT\_MCTrain}_{\,j}{*}CESCS_{ij}) + \Upsilon_{13}(Mean\_Exp_j{*}CESCS_{ij}) + \Upsilon_{20}(IMMIG_{ij}) + \Upsilon_{21}\,(MU\_ESCS_j{*}\ IMMIG_{ij}) + \Upsilon_{22}\,(\mathrm{PCT\_MCTrain}_{\,j}\ IMMIG_{ij}) + \Upsilon_{23}(Mean\_Exp_j\ IMMIG_{ij}) + \mu_{1j}(CESCS_{ij}) + \mu_{2j}(IMMIG_{ij}) + \mu_{0j} + \mu_{1j} + e_{ij}$

Results using data with USA immigrant students only:

Model:	M0	M1	M2
Fixed part[a,b]	**Coefficient (s.e.)**	**Coefficient (s.e.)**	**Coefficient (s.e.)**
Intercept	481.63* (4.46)	480.05* (5.15)	526.42* (21.73)
CESCS		21.74* (3.73)	16.48 (16.32)
MU_ESCS		14.13* (5.9)	
MU_ESCS CESCS*		9.67* (3.80)	
PCT_MCTrain			-.58* (.25)
*PCT_MCTrain*CESCS*			.04* (.19)
Random part[a,b]			
σ^2_e	7,347.84* (315.15)	7,020.89* (305.95)	7,034.81* (307.81)
$\sigma^2_{\mu 0}$	1,478.09* (315.11)	710.11* (115.73)	728.72* (223.94)
$\sigma_{\mu 0\, 1}$		132.04 (89.03)	227.88* (96.39)
$\sigma^2_{\mu 1}$		143.83 (103.87)	192.00* (112.95)
Deviance	14,417	14,339	14,346

Curriculum Vita

Ariana Audisio is a native of Brazil but was raised in Venezuela by a Venezuelan mother and an Italian father. After studying Economics at the Catholic University "Andrés Bello" in Caracas, Venezuela, she worked for 3 years as a Research Associate at the Venezuelan Institute for Scientific research, assisting in all steps of the research process in two main projects: International Competitiveness of Venezuelan Agro-Food Chains; and Public Policies, Environmental degradation, and Rural Poverty. After emigrating to the United States, she participated in the education sector as a teacher, parent and volunteer. Ariana is a degree candidate with the Johns Hopkins University for a Master of Science in Government Analytics, and lives in Rockville, Maryland with her husband and children.